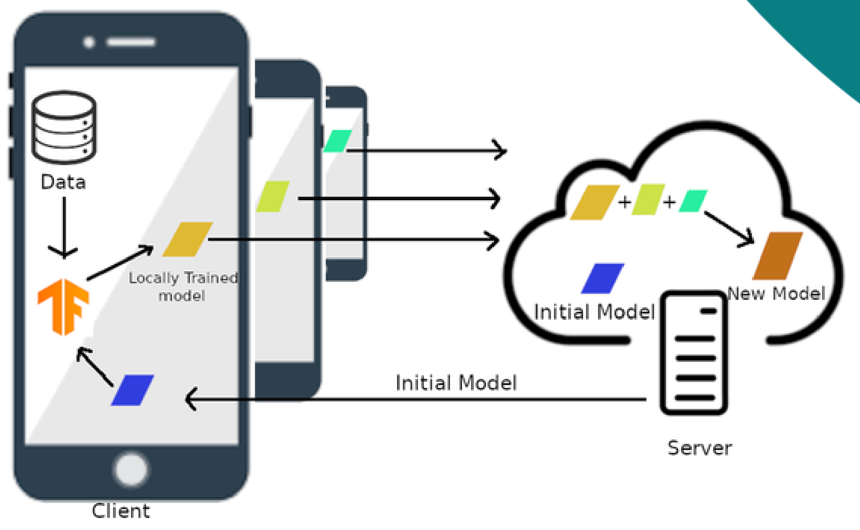
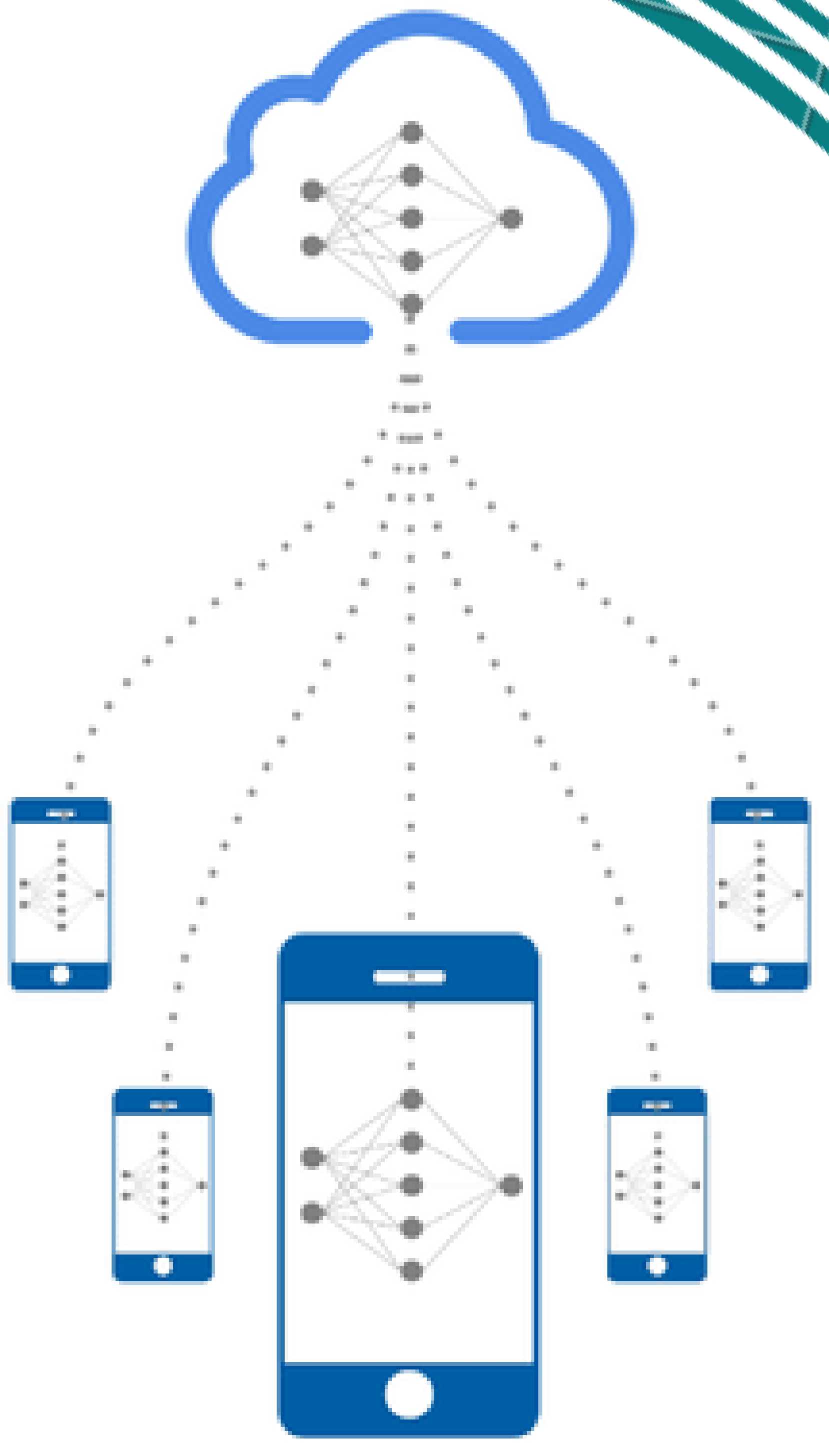




LifeFedAI

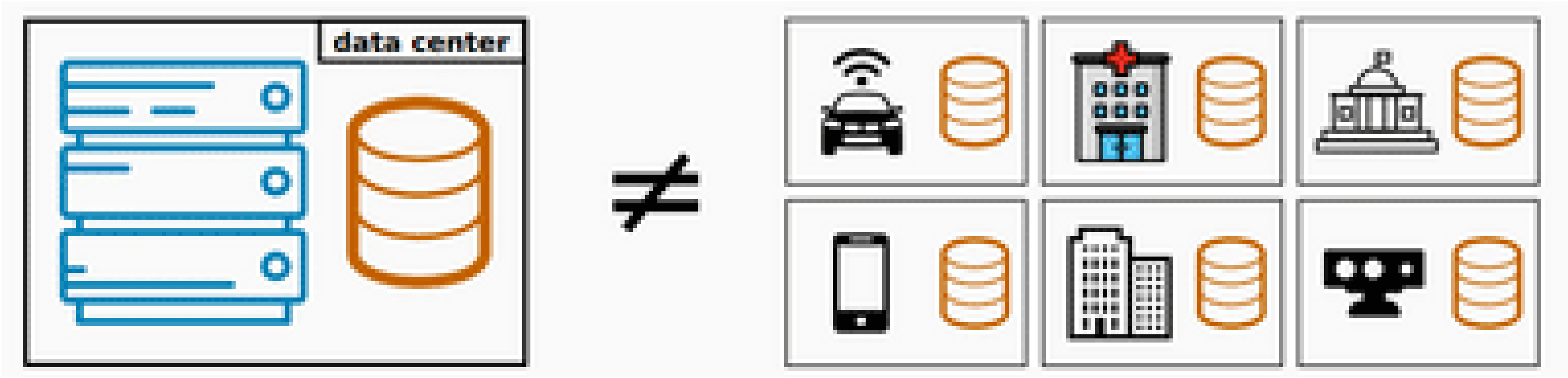
CodeAI

Federated Learning – A Decentralized Form of Machine Learning

Federated Learning is born at the intersection of on-device AI, blockchain, and edge computing/IoT.

The standard setting in Machine Learning (ML) considers a centralized dataset processed in a tightly integrated system. But in the real world data is often decentralized across many parties.

But in FL, we train a centralized Machine Learning model on decentralized data.



WHY CAN'T WE JUST CENTRALIZE THE DATA?

1. Sending the data may be too costly. Huge amount of data can be produced. Some wireless devices have limited bandwidth/power.

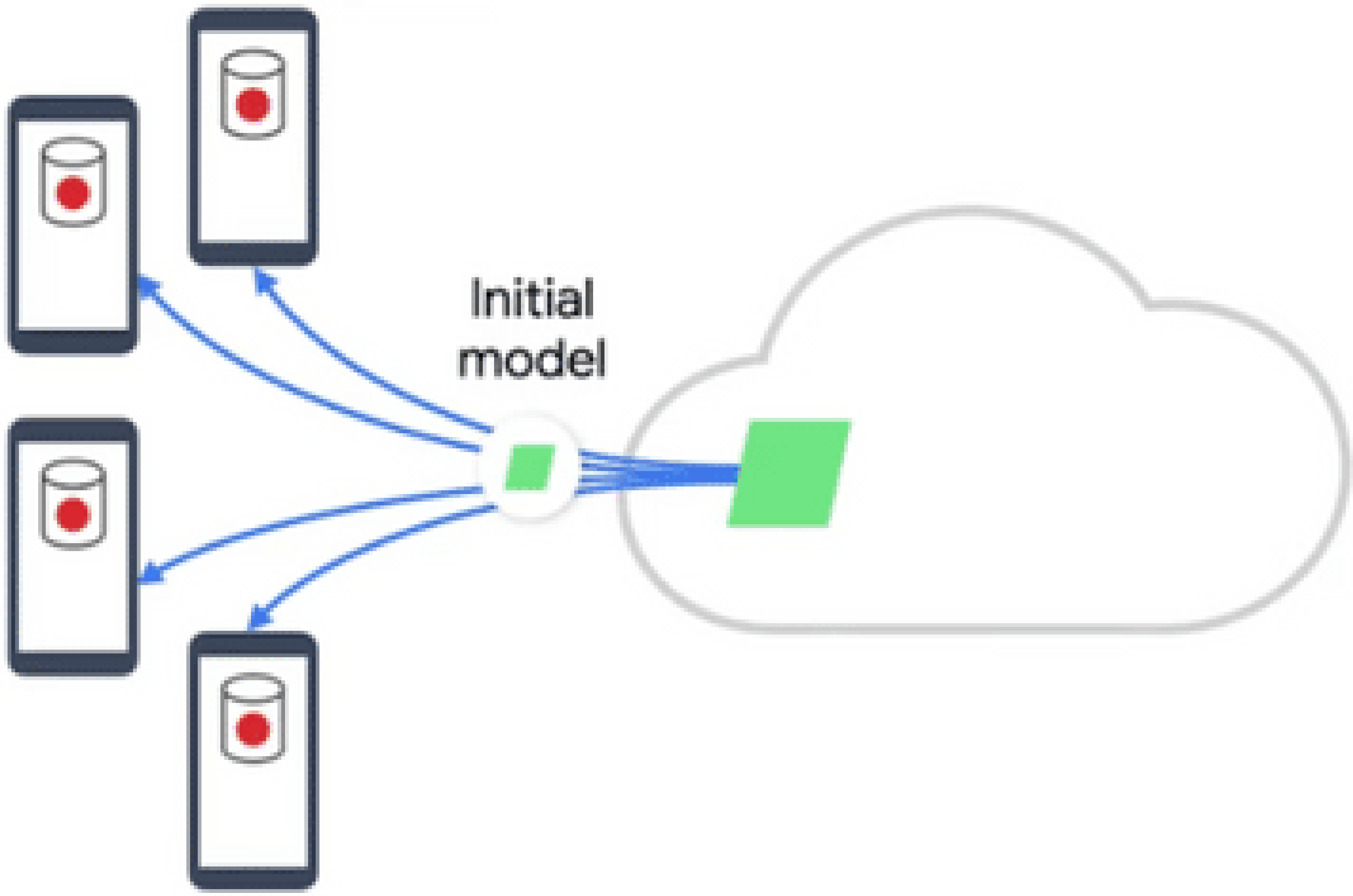
2. Data may be considered too sensitive. Public awareness and regulations on data privacy. Keeping control of data can give a competitive advantage in business and research

HOW ABOUT EACH PARTY LEARNING ON ITS OWN?

1.The local dataset may be too small. Sub-par predictive performance (e.g., due to overfitting). Non-statistically significant results (e.g., medical studies)

2.The local dataset may be biased • Not representative of the target distribution

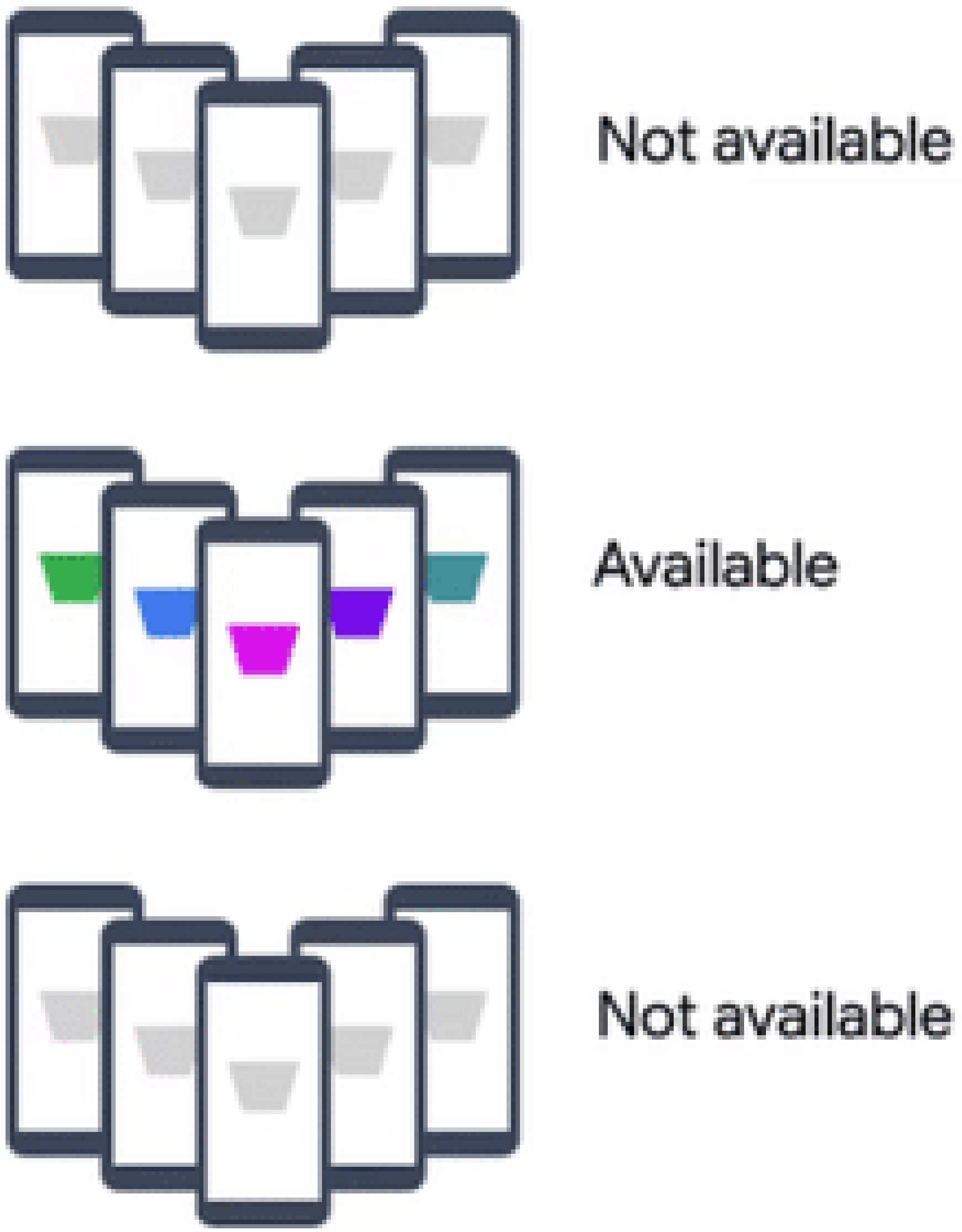
Working of FL



STEP 1

An initial model Sent from server to client

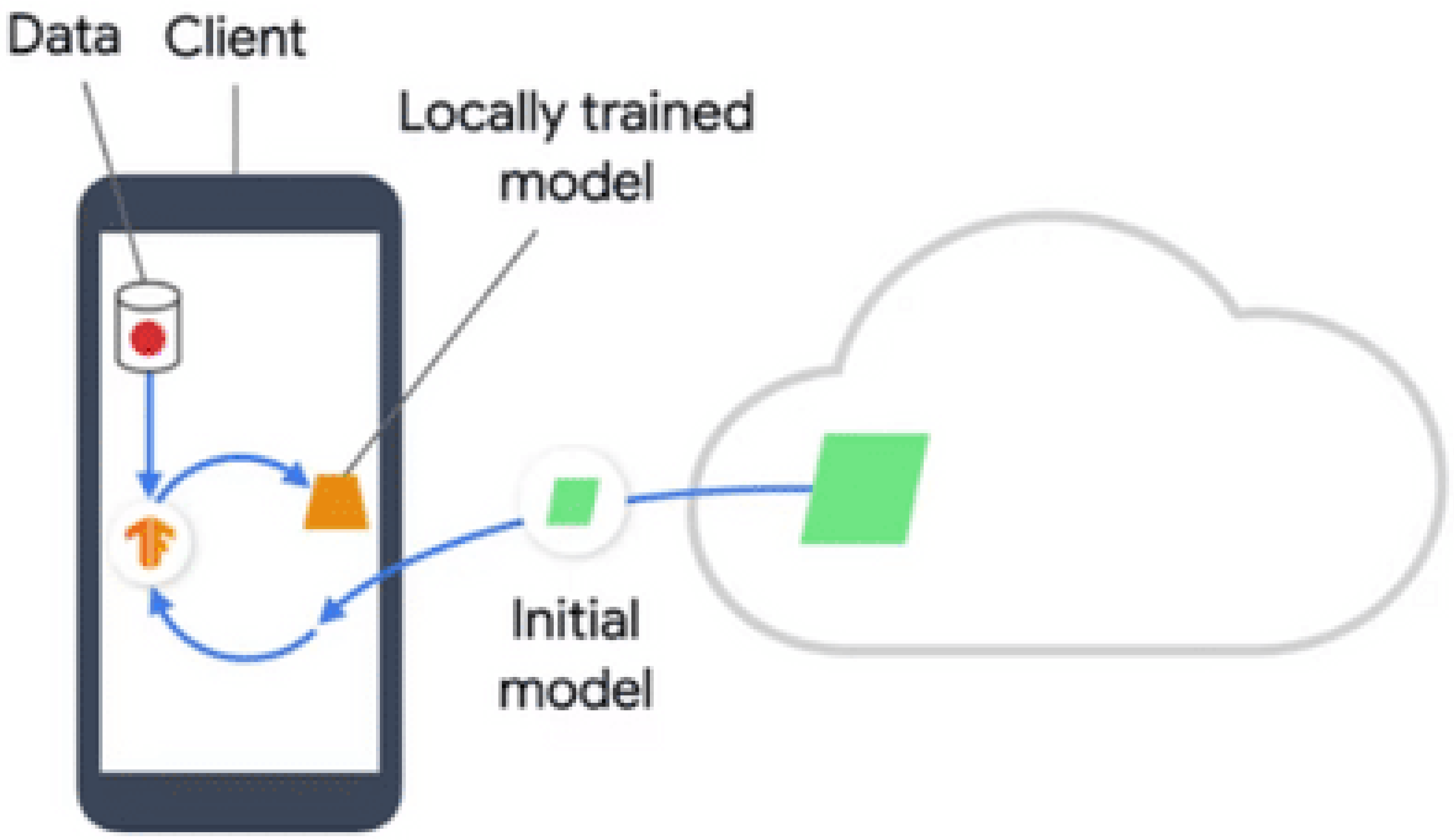
Working of FL



STEP 2

Server identifies which client available, suitable device, To improve user experience

Working of FL

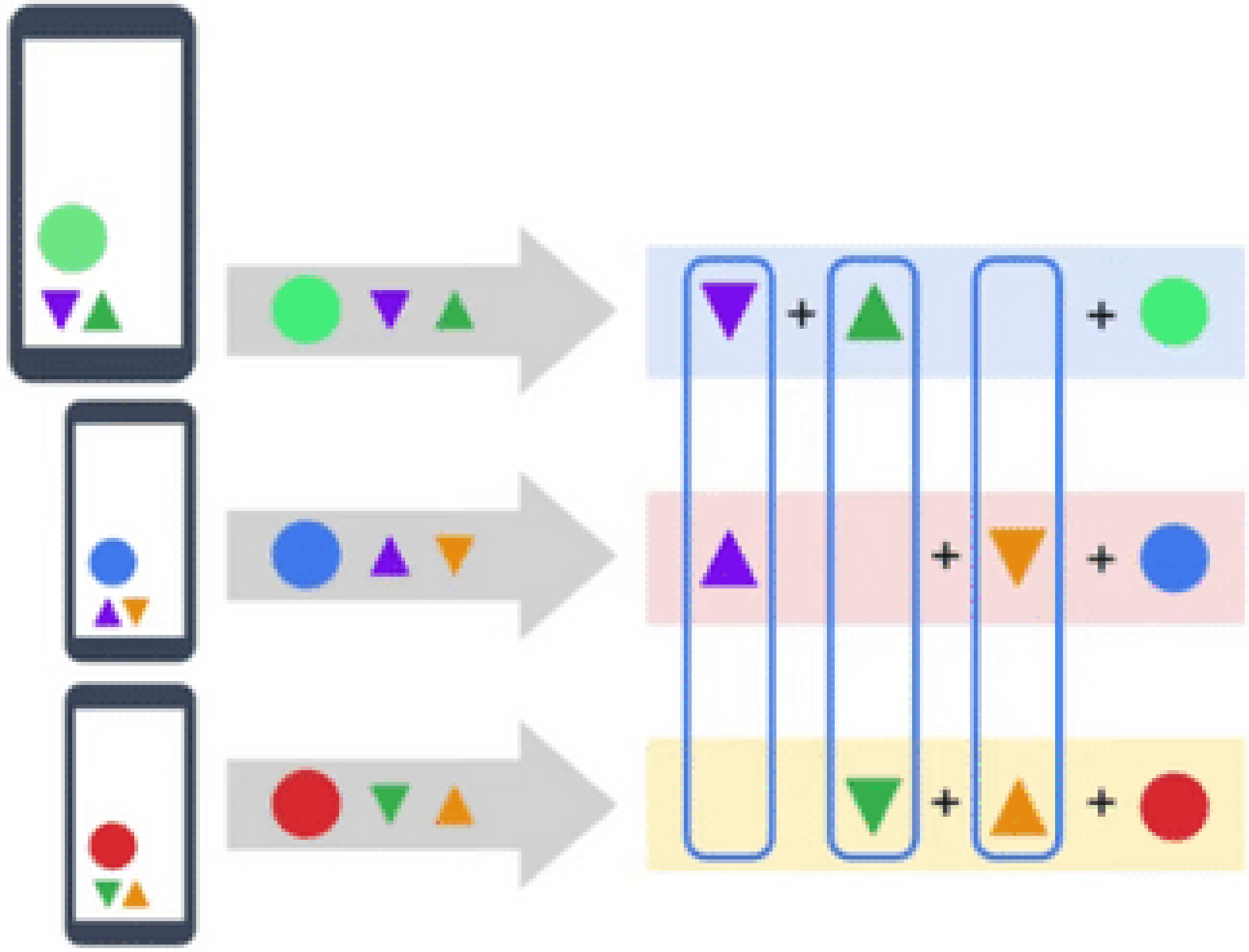


STEP 3

The model from server is locally trained in the device with the model in the device.

Secure aggregation

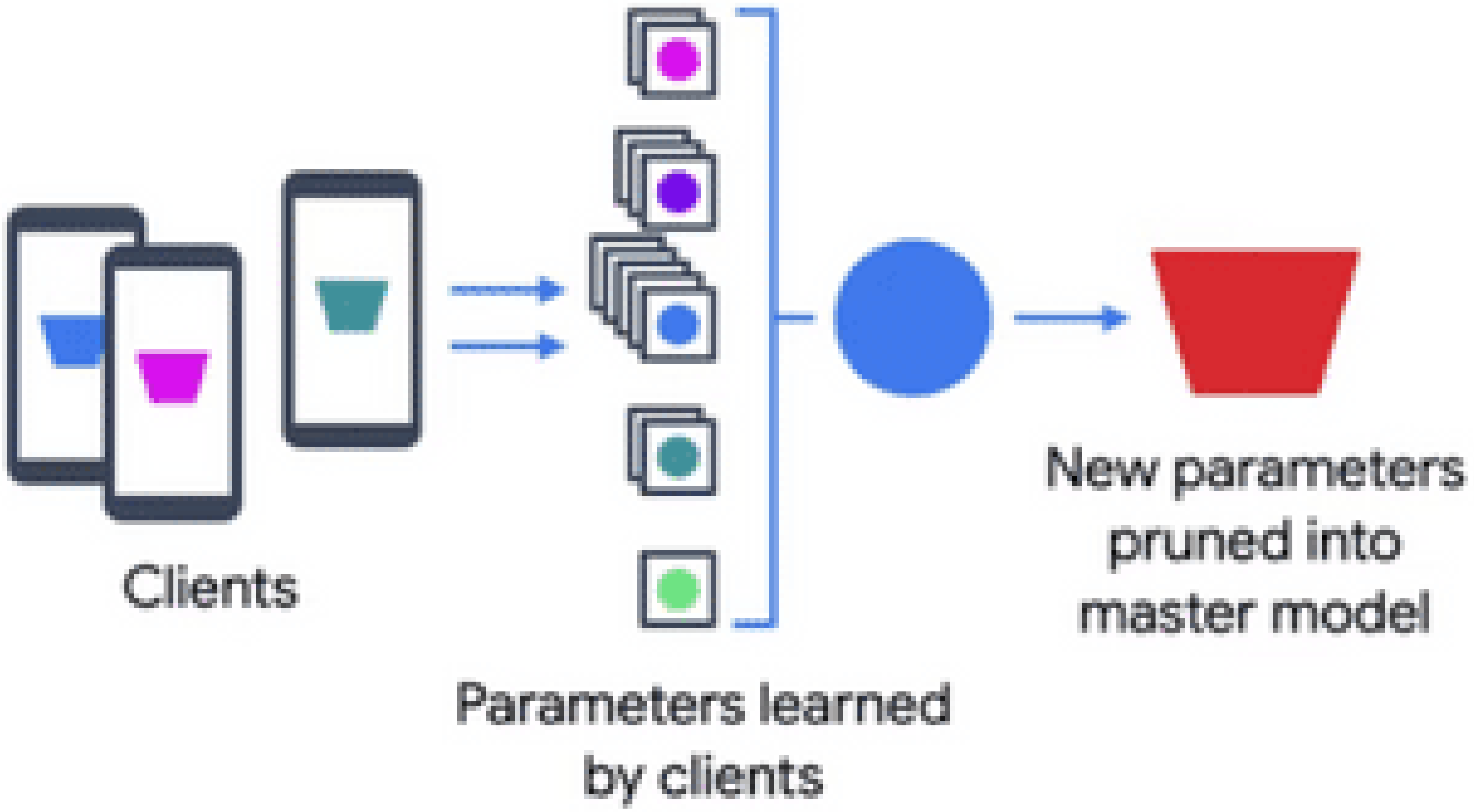
STEP 4



Buddy system= data from each device can be combined with random values, then sent to server. The server knows the values and eliminates the buddy values

Create a system that encrypts the user-sensitive data with an encryption key that is not in the hands of our centralized cloud server. Such an approach is referred to as the **Secure Aggregation Principle**, where our server is allowed to secure and combine the encrypted results and decrypt only the aggregated results.

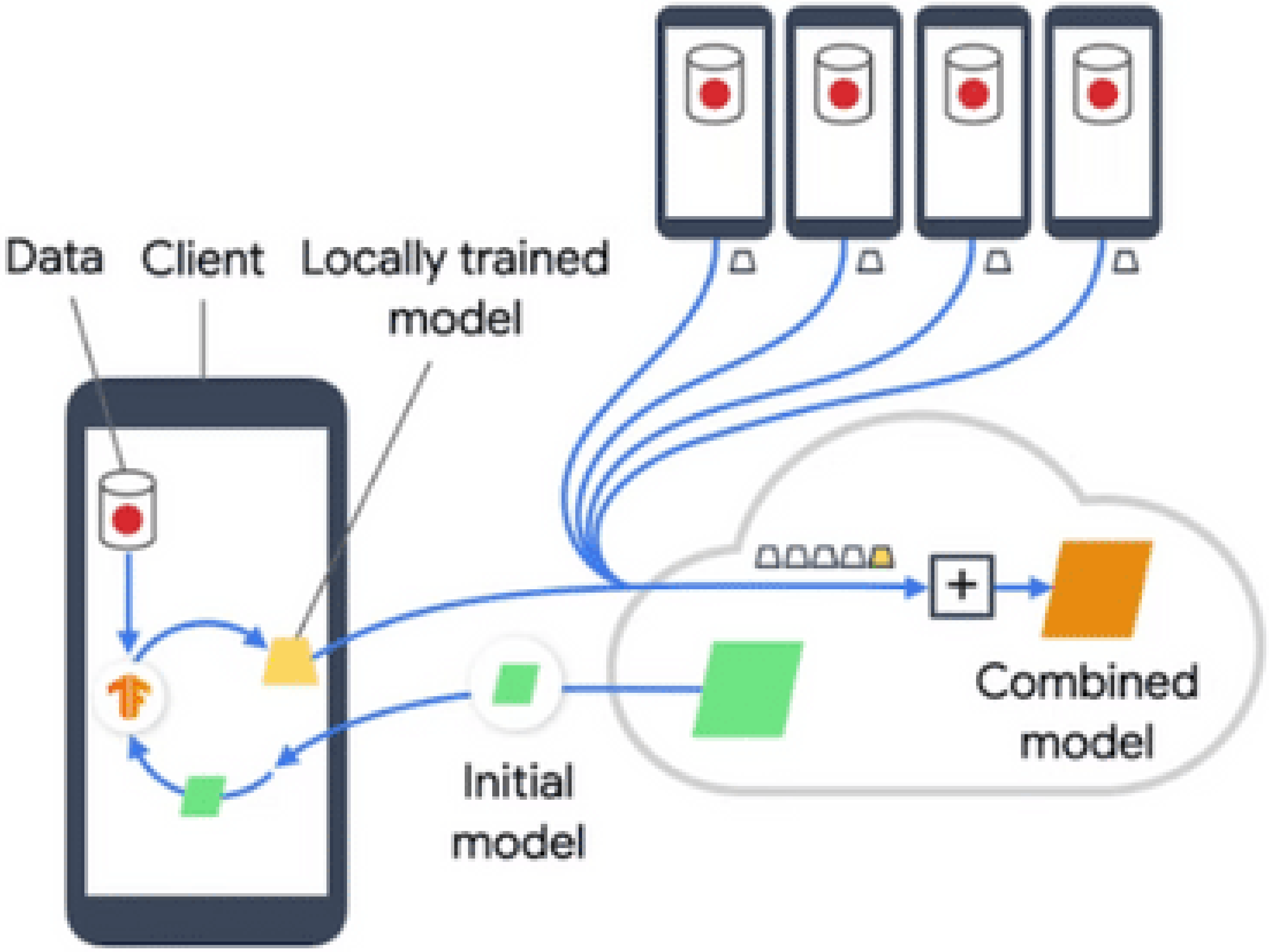
Working of FL


Clients
Parameters learned by clients
New parameters pruned into master model

STEP 5

Weight, biases, other parameters learnt by model leaves the individual devices, data does not leave the device, hence privacy maintained.

Working of FL



STEP 6

The trained models from all devices are sent to the server and all models are combined using certain algorithm and the final model is prepared.

Federated Average Conditional Mutual in Alzheimer’s Detection

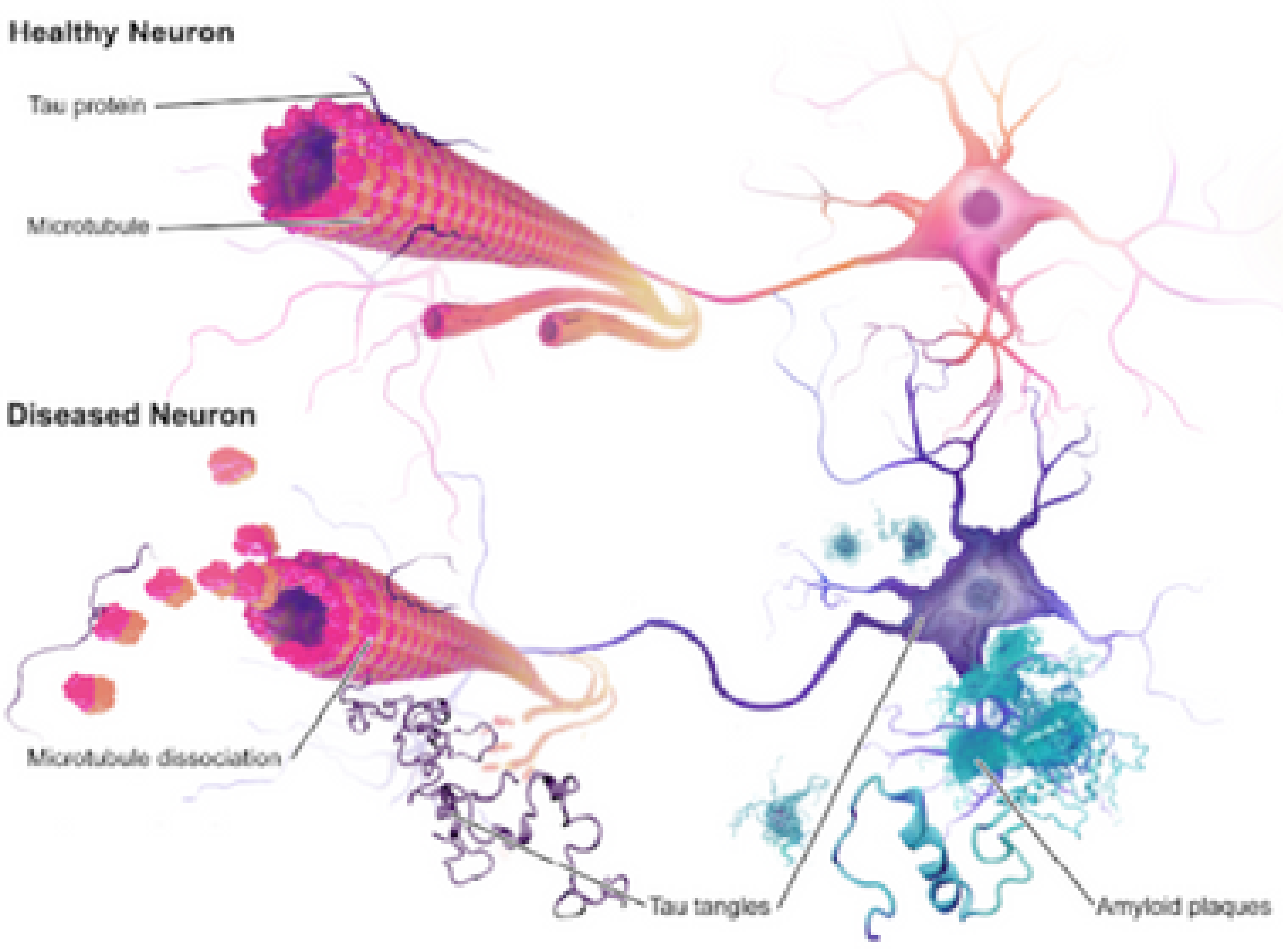
Problem Statement

Alzheimer's Disease

Alzheimer disease (AD) is a neurological disorder. For the AD, there is no specific treatment. Early detection of Alzheimer’s disease can help patients receive the correct care. Many studies employ statistical and machine learning techniques to diagnose AD.

Why is it a concern?

- At later stages, AD is difficult to prevent from further growth.
- AD is often misunderstood as age related issues.
- Diagnosis of AD is very costly and has side effects.
- Predicting early helps save the patient from extreme adverse conditions



Proposed System

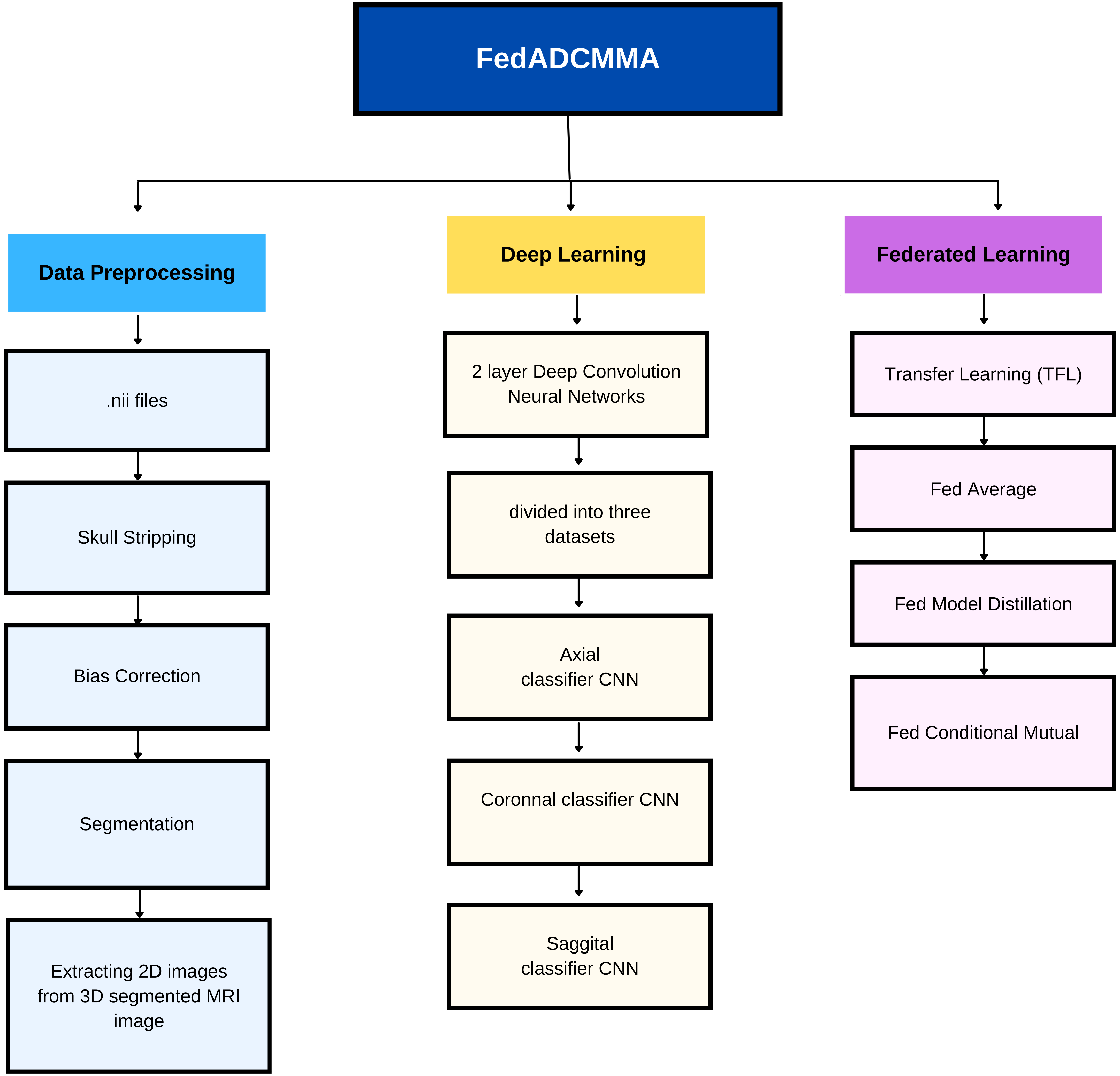
In this work, we propose a **FedACM learning Algorithm** (***Federated Average Conditional Mutual Learning***) to improve the performance by considering *decentralized data* of clients, model training by *averaging the parameters* learnt by each model from client after returning to server and model distillation helps learning for individual client models through *mutual consensus knowledge distillation* while *preserving data privacy* and finally conditional mutual learning helps considering the clients' *local performance* and the similarity between clients and mutual learning *improving performance*.

Advantages:

- Decentralized data
- model training by averaging the parameters
- mutual consensus knowledge distillation while preserving data privacy
- considers local performance and similarity to improving performance

Proposed System Architecture

FedADCMMA



FedADCMMA

Data Preprocessing

.nii files

Skull Stripping

Bias Correction

Segmentation

Extracting 2D images from 3D segmented MRI image

Deep Learning

2 layer Deep Convolution Neural Networks

divided into three datasets

Axial classifier CNN

Coronnal classifier CNN

Saggital classifier CNN

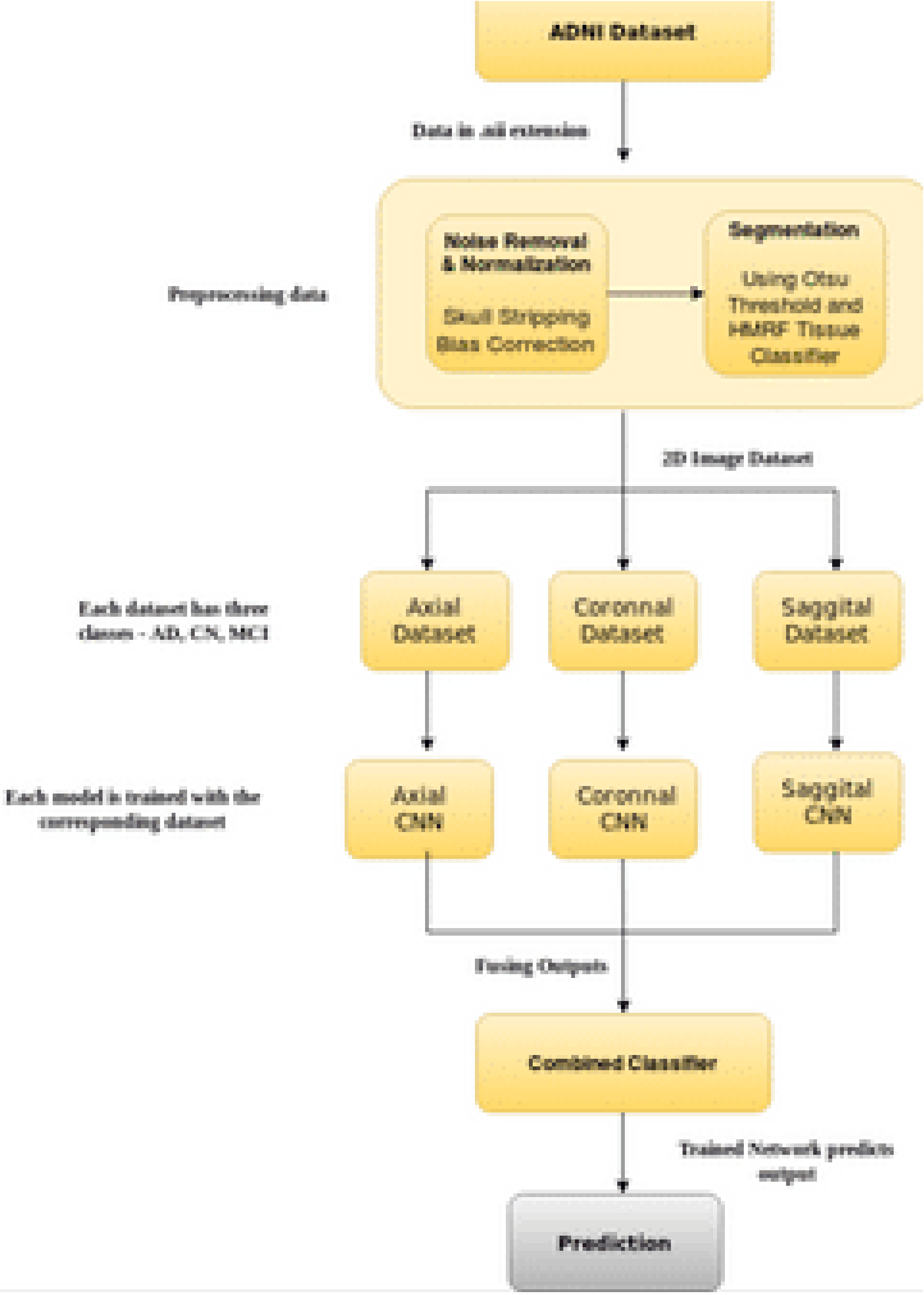
Federated Learning

Transfer Learning (TFL)

Fed Average

Fed Model Distillation

Fed Conditional Mutual



The above figure shows the architecture for multiple classifier. Here, the method is similar to the previous approach till the pre-processing phase.Once the dataset is produced, it is divided into three datasets so that each dataset consist of only one kind of data. In this manner, the complexity of the problem is reduced. Each of the dataset is then fed into three **seperate classifiers - Axial, Coronnal, Saggital**(each of which is a Simple CNN Architecture).

Django Web Application for user use.

Demerits of existing systems

- In existing models average consensus lacks the ability to handle site-wise heterogeneity

- Not well-adapted to individual client due to the data size variability.

- Malicious members can update the fallacious weight to mislead the update direction or reconstruct other members’ data.

- Lack of Fair Resource Allocation.

- Different datasets, which are stored at different institutions, cannot always be shared directly due to privacy and legal concerns.

- A model is fitted without sharing individual information across centers, but only model parameters, and not any statistical analysis and performance checking.

Datasets

ADNI - Alzheimer’s Disease Neuroimaging Initiative

MRI and PET images, genetics, cognitive tests, CSF and blood biomarkers as predictors of the disease

Kaggle

https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images

https://docs.google.com/document/d/1KRUT1XOJN6xrGYydb_oS5jbVPJ68d-VkdI2zaSoHMrg/edit?usp=sharing

FED ALGORITHMS USED

Federated Algorithms Used

- **Transfer Learning(TFL):** The base 2DCNN is pre-trained on public dataset, then fine-tuned on private sample dataset.
- **FedAvg:** The knowledge is exchanged by periodically updating the model initialization weights with the average model weights from every clients.
- **FedMD:** The knowledge is exchanged by distillation through the average logits of each clients on public dataset.
- **FedCM:** To compare the effectiveness of two conditioning terms, we construct FedCM with entropy ratio conditioning.

Syft an PyTorch for FED Code

Diabetes Prediction

DATA

Kaggle Data set - Diabetes.csv

ALGORITHMM AND MODEL

I made a django application which uses the RandomForest algorithm to detect whether the individual has diabetes or not from the data input by the user.

Heart Disease Prediction

DATA

Kaggle Data set - HeartDisease.csv

ALGORITHMM AND MODEL

I made a django application which uses the RandomForest algorithm to detect whether the individual has heart disease or not from the data input by the user.

Breast cancer Prediction

DATA

Kaggle Data set - uciml/breast-cancer-wisconsin-data

ALGORITHMM AND MODEL

Detection using KNN, SVM, Naive Bayes, Decision Tree, RandomForest and checking the accuracy.
I made a django application which uses the KNeighborsClassifier algorithm to detect whether the individual has breast cancer or not from the data input by the user.

Thank You